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Empirics of technology and unemployment in advanced countries(1)

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Abstract. *This study is the first attempt to investigate the empirical relation between progress in technology and unemployment of high and low skilled workers at macro level. Although there is substantial literature on the theory to associate unemployment with technology, empirical analysis of the relation is rare. The theoretical background is split between two opposing assertions: On one side, technology is claimed to increase unemployment since more advanced technology replaces labor, especially in advanced countries where the cost of labor as wages is too high. On the contrary, technology is supposed to cause the enlargement of the already existing sectors and the formation of new industries. We established a model to check for the existence of a cointegrating relation between technology and unemployment using additional control variables with Pedroni's (1999, 2001) methodology. After securing our model's adequacy, we report that technology leads to more unemployment, even in developed countries. On the other hand, we detailed the analysis by searching for the nature of the same relation with high and low skilled workers. Our estimation results revealed that the relationship is somewhat different for these skill groups.*

Keywords: technology, unemployment, skill groups, Pedroni cointegration, Panel DOLS, FMOLS.

JEL Classification: E24; J64; O32; O33.

1. Introduction and motivation

As patent applications worldwide reached 3.3 million in 2018, proving credit to Schumpeter's "Creative Destruction", the answer to the simple question, "Does technology reduce unemployment?" attracts more attention of economists and workers (WIPO, 2019). Since the very definition of technology is characterized by producing the same commodity/service less costly, technology saving more labor force leads to unemployment. That is why Ricardo's "working class" had signaled their fear of being dismissed due to innovation by destroying machines under the lead of Ned Ludd (Vivarelli, 2014). On the other hand, from a wider perspective technology enables new industries in which more workers will be employed. As Steuart put it in 1966, "The introduction of machines is found to reduce prices in a surprising manner. And if they have the effect of taking bread from hundreds, formerly employed in performing their simple operations, they have that also of giving bread to thousands". This argument is positive for the entire workforce and is correct but the ones losing their jobs are not the ones receiving "thousands of bread". A pervasive look at processes and mechanisms is required to come up with a clear answer to the seemingly simple but perplexing question posed. The following items exemplify processes leading to both more or less employment and the net effect of technological progress depends on whether such employment creating processes outweigh the others or not:

- Technological progress has to result in the output of a better product at a lower cost. Assuming that the market has the characteristic of competitiveness, the decrease in total cost will be transferred to price decrements, which will increase the demand for the commodity. To meet with higher demand, extra output asks for more employment.
- As new investment in machinery, equipment, and infrastructure is inevitable to innovate and advance technology, more workers are required.
- A huge investment in R&D aims to replace workers with automated machines, which will directly yield more unemployment.
- Workers laid off due to technological progress cannot demand as much as they used to; this will lead to a decrease in aggregate demand and a further increase in unemployment.
- As the commercialization of new products will be spread worldwide, manufacturing of all such products will invite more labor and an increase in total output due to the introduction of new products and the upgrade of existing ones.
- As more advanced technology will be implemented, some workers' wages will decrease, and demand for a cheaper workforce will be more. In return, less earning workers will demand less resulting in less output and thus employment. On the other hand, a specialized workforce will be paid more, and they will increase aggregate demand leading to more output and employment.
- The application of innovation increases productivity, which will be reflected in wages and GDP per capita. This will increase demand and in turn employment.

Corresponding literature addresses these and many other similar arguments to come up with a satisfactory answer to the question posed at the beginning in addition to several aspects of technology unemployment relation. Vivarelli (2014) highlights an extensive literature survey indicating both sides of the controversy. Although innovative developments in other areas such as organizational structure, quality in financial services, and management style should be taken into consideration, they have been the subject of empirical works recently. Milgrom and Roberts (1990), Bresrahan et al. (2002), and Bloom and Von Reeren (2010) show that developing and changing organization structures and management styles are important factors in increasing qualitative and quantitative levels of employment. Collard and Dellas (2007) use the international Real Business Cycle (RBC) model to show that the reaction of employment to a technology shock is negative in case the degree of substitution between domestic and foreign goods is low.

Several critical studies in the literature focus on what percentage of existing jobs will destroy or not require the labor force in the future because of technological advancement. Frey and Osborne (2013, 2017), one of the most important of these studies, state that in the next two decades, 47% of the existing jobs in the USA will be replaced by technological machines due to digitalization and the remaining works will be more related to creative or social intelligence. Bowles (2014) adapts this study to European countries and states that job loss due to information and communication technologies (ICT) may reach 60% in the coming decades. Bonin et al. (2015), with a more optimistic estimate, suggest that the rate of technology-related job losses in Germany will be 12% in the future. Bonin et al. (2015) indicate a lower negative impact of technology on employment because he also considers technology-based new business opportunities while Frey and Osborne (2013) and Bowles (2014) ignore the job opportunities due to technology advancement. In other studies, such as the Boston Consulting Group (2015) and Wolter et al. (2015) that have made optimal estimates of technology's impact on employment, it is also emphasized that there will be severe structural changes in the production sector especially with Industry 4.0. However, considering the new job opportunities created by technology improvements, the negative effect on the overall number of employees will be shallow.

Acemoglu and Restrepo (2020), one of the most recent studies on this subject, examines industrial robots' impact on employment in U.S. Labor Markets. They conclude that a one-unit increase in the number of robots per thousand workers decreases employment by 0.2% and average wages by 0.42%. They also state that the number of robots in the future will be 5.25 times more for every thousand workers according to the Boston Consulting Group (2015) estimates; in this case, total employment will decrease by 1% between 2015 and 2025.

As noted in Matuzeviciute et al. (2017), although there are many studies at the micro and sectoral levels, macro-level empirical studies are limited. Besides, most of the macro-level papers focus on the overall impact of technology on unemployment. While this impact is positive in three out of the eight most recent studies, no significant findings are reported by four papers. Feldmann (2013) uses Triadic Patent Families as the core independent variable and finds that the relationship between employment and technology is negative, which means technological progress increases unemployment. Matuzeviciute et al. (2017) achieve different results using similar countries and variables.

The technology-employment relationship should not be considered as one-dimensional but be examined with diverse groups and proxies. Although there are many studies at micro and sectoral levels, there is no empirical study at the macro level in the literature, which examines different skill groups to the best of our knowledge. Since the interaction of high and low skilled workers to technology is different, skill-biased technology shocks have different ultimate impacts on the productivity and thus skill premium of the two. Because many of the technology shocks are skill-biased instead of being neutral, low-skilled workers are disadvantaged. Michaels and Graetz (2015) examine the influence of new automation systems on employment at the micro-level for 17 countries between 1993-2007. They do not detect significant evidence of an adverse effect of technology on total employment, only a negative effect on low-skilled employees and a smaller effect for middle-skilled workers.

Many studies on the direction and intensity of the relationship between technology and unemployment so far have achieved inconsistent results. But today, discussions about the effect of technology on employment have reached a different dimension. The new machines, computers, software, and other innovations developed in various sectors and industries, while offering new business opportunities, destroy some of the existing professions leading to structural unemployment. We are familiar with ready-made meal suppliers who do not have a restaurant, clothing vendors who do not have a real store, and R&D departments are currently working on driverless cars and mail delivering drones. Does this mean people working in these sectors will be removed entirely from the business world? Or, as some economists have argued, does technology bring many advantages and always compensate the damages with new job opportunities? A key feature of the laborers is the qualification of the employee.

Much consideration was paid to skill-biased technological shift that is first empirically explored by Berman et al. (1994), who proves the existence of a strong correlation between industry skill upgrading and increased investment in computer technology and R&D in the U.S. manufacturing sector. Mortensen and Pissarides (1999) establish a theoretical model to answer “Do skill-biased shocks that increase the spread of labor productivity interacting with different policy regimes, explain the rise in unemployment in Europe relative to the United States in the 1980s and 1990s?”, but do not touch on the empirics. Similarly, Pieroni and Pompei (2007) explore the link between labor market flexibility and innovation, paying particular attention to different technological regimes of economic activities and different geographic areas of the Italian economy in a micro framework. According to Caselli and Coleman (2006), developed economies have a more intense high-skilled labor force than developing countries so that they can adapt labor markets more easily to technological changes. On the other hand, Acemoglu and Autor (2011) state that especially routine jobs require fewer human resources due to skill-biased technological changes.

According to the report published in the World Economic Forum (2018), 71% of total work hours in 12 industries are performed by humans, while machines carry out 29%. In the same report, it is estimated that the share of machines in labor hours will increase to 42% by 2022. So, do these predictions mean that total employment will shrink? The report explains that the existing 75 million jobs will move from people to machines; in other words, technology “will destroy” employment. On the other hand, 133 million new job opportunities will arise due to technology. However, the critical point here is to what extent the existing human resources will be able to adapt to new business opportunities to be created with the qualifications they currently have. It is difficult to predict at what speed employees will upgrade themselves but identifying how high-skilled and low-skilled workers are affected by technology at the macro level in developed countries will make a significant contribution in this area. Although there are considerable studies in the micro-framework, macro analyses are rare, and among them, none is focusing on the list of countries we explore, over the period we study, with the methodology we facilitate, and the emphasis on skill-biased employment. With these four features stated, our research is unique to fill the gap in the literature. The outline of our paper includes the Introduction and Motivation in Section 1 followed by Section 2 highlighting data and methodology we use in detail. Section 3 reports estimation results and interprets them. Finally, Section 4 concludes with remarks.

2. Data and methodology

The main aim of the study is to document how the unemployment rates of developed countries are affected by technological advances and to determine whether the relationship between these two variables changes with skills. For this purpose, the unemployment rate is used as the dependent variable in the first three models, while in the other four models, high-skilled and low-skilled employment rates are on the left-hand side of the equations. The abbreviations, explanations, and units of the variables are portrayed in Table 1. All dependent variables are in percentages. The unemployment rate refers to the ratio of the population not working in the country to the total labor force in accordance with the International Labour Organization (ILO) definition. Employment rates by skill levels indicate the percentage of laborers by skills in the total labor force. ILO scaled the skill levels from 1 to 4, combining groups 3 and 4 as “high skill” and named groups 1 and 2 as low ’and’ medium, respectively. In this study, “low” and “medium” groups are combined, and the “low-skilled employment” group is formed and identified into a single variable. Research and Development (R&D) expenditure, which is the core independent variable of the study, and GDP are used as per capita in constant USD. Output per worker, which is derived from the ILO database, is used as a productivity measure, and it is also in the form of constant USD. Besides, variables such as consumer price index, public unemployment spending, trade union density, real effective exchange rate index, and real interest rate are also identified as independent variables. The baseline panel equation specified in this direction is:

$$U_{it}=\alpha_0+\beta\ln(RD)_{it}+\alpha_1\ln(GDP)_{it}+\alpha_2\ln(CPI)_{it}+\alpha_3\ln(PRD)_{it}+e_{it} \tag{1}$$

Where subscript i stands for country and t for time for the following variables: U (Unemployment rate), RD (research and development expenditure per capita), GDP (the real GDP per capita), CPI (consumer price index), and PRD (a measure of productivity – output per worker). Finally, e_{it} is an error term including other factors that affect unemployment. Other macroeconomics variables such as *INT (*real interest rate), *EXC* (real effective exchange rate index), *TUD* (trade union density index), and *PUS* (public unemployment spending per capita) are also used in additional models.

Table 1. *List of variables*

Description and Units of Variables	Symbol	Source
Unemployment rate (% of total labor force)	U	ILO (2020)
High-skilled employment rate (% of total labor force)	HSE	ILO (2019), authors' calculations
Low-skilled employment rate (% of total labor force)	LSE	ILO (2019), authors' calculations
R&D Expenditure per capita (constant 2010 US$)	RD	OECD (2020), authors' calculations
GDP per capita (constant 2010 US$)	GDP	World Bank (2020)
Consumer price index (2010 = 100)	CPI	World Bank (2020)
Productivity (output per worker: constant 2010 US$)	PRD	ILO (2020), authors' calculations
Public unemployment spending per capita (constant 2010 US$))	PUS	OECD (2020)
Trade union density index (2010 = 100)	TUD	OECD (2020), authors' calculations
Real effective exchange rate index (2010 = 100)	EXC	World Bank (2020)
Real interest rate (%)	INT	World Bank (2020), authors' calculations

Although the coefficient and sign of RD_{it} are mainly questioned; there is no consensus on it as stated in the empirical and theoretical literature review. Theoretically, the effect of GDP on unemployment is negative, and studies based on Okun's Law claim that, in general, high growth rates are associated with high employment. The findings on the relationship between productivity and unemployment are different. According to Landmann (2004), employment and productivity are positively correlated with a pro-cyclical pattern. However, Barnichon (2010) argues that before the 1980s, the relationship between technology and unemployment is negative but weak, while it is positive and strong after the 1980s because of the technology shocks. In addition, due to the nature of the "output per worker" variable used in productivity measurement, a negative reflection of productivity growth on employment is always a strong possibility. The overall effect, therefore, depends on the extent to at what level is productivity translated into new investments and business opportunities in the long run.

Even though the traditional representation of the inflation-unemployment relationship is mostly based on research by Philips (1958), and Samuelson and Solow (1960), Škare and Caporale (2014) find that long-term employment is negatively affected by inflation. Feldman (2010) also indicates that high inflation causes a decline in investment and economic growth, which means lower employment in the long run. Similar to these investigations, many empirical studies are indicating that employment is negatively affected by inflation in the long run. Economic theory and empirical studies such as Nickell et al. (2005) suggest that public unemployment spending decreases the desire to search for a job. Thus, an increase in unemployment benefits means higher unemployment rates.

Trade union density indicates the proportion of employees belonging to a trade union in the country. Soskice (1990), Blanchard and Wolfers (2000), and Baccaro and Rei (2007) state that high trade union density leads to high unemployment rates. The effect of reel-effective exchange rate on unemployment is discussed in the literature differently. Frenkel and Ros (2006), Frenkel and Taylor (2009), Bakhshi and Ebrahimi (2016), and He (2013) underline that there is a negative linkage between the exchange rate index and unemployment. Finally, for the real interest rate, since the higher real interest rate means lower investment and labor demand, theoretically, interest rate and unemployment are positively correlated. Also, empirical studies such as Blanchard and Wolfers (2000) and Feldmann (2013) indicate that in the long run, a higher real interest rate decreases employment.

Table 2 recaps descriptive statistics of 21 developed countries for both high and low skilled labor between 1990-2019. The average per capita GDP of these 21 countries is approximately \$45,354, and per capita R&D expenditure is almost \$948. Besides, the average unemployment, high-skilled employment, and low-skilled employment rates are 7.38%, 36.25%, and 56.34%, respectively. Northern European countries such as Norway, Sweden, Finland, and Denmark have the highest per capita R&D expenditures, in addition to Switzerland. In these countries, the share of high skill employment rate in the total labor force is around 40%. Moreover, the overall unemployment rate in these countries is 7.56%.

We go one step further and estimate the following specifications to work out the unemployment rates of low and high-skilled labor.

$$HSE_{it}=\alpha_0+\beta\ln(RD)_{it}+\alpha_1\ln(GDP)_{it}+\alpha_2\ln(CPI)_{it}+\alpha_3\ln(PRD)_{it}+e_{it} \tag{2}$$

In Eq. (2), the dependent variable is High Skill Employment (HSE_{it}) whereas the independent variables are the same as in (1). We expect to return a positive coefficient of RD_{it} as opposed to the one in the first three equations. Both the skill-biased technological change approach and findings on the relation between job polarization and technology underline new job opportunities for high-skilled workers. Theoretically, a rise in GDP should increase the rate of high-skilled employment. However, our expectations of the coefficient signs for the other variables are not that clear. Unemployment benefits, for instance, demotivates typical laid-off workers to search for a job, but for high-skilled workers, the fringe benefits provided by companies offset this demotivation.

$$LSE_{it}=\alpha_0+\beta\ln(RD)_{it}+\alpha_1\ln(GDP)_{it}+\alpha_2\ln(CPI)_{it}+\alpha_3\ln(PRD)_{it}+e_{it} \tag{3}$$

Table 2. *Descriptive statistics*

Country	Statistics	U (%)	HSE (%)	LSE (%)	RD ($)	GDP ($)	Country	Statistics	U (%)	HSE (%)	LSE (%)	RD ($)	GDP ($)
AUT	Mean	6.58	38.84	54.48	902	47053	JPN	Mean	3.75	22.33	73.91	1324	43519
	Std. dev.	1.84	3.50	2.08	287	7365		Std. dev.	1.03	1.81	2.26	203	3095
	Max.	10.87	43.53	57.76	1336	57071		Max.	5.37	24.89	78.52	1620	49188
	Min.	4.23	33.42	51.31	452	35035		Min.	2.09	19.39	71.64	993	38074
AUS	Mean	4.80	33.33	61.85	1013	43252	NLD	Mean	4.90	45.05	49.97	872	46785
	Std. dev.	0.74	4.37	4.86	386	5346		Std. dev.	1.61	2.00	1.00	150	6203
	Max.	6.01	38.97	70.50	1641	50655		Max.	7.42	47.63	52.79	1226	55690
	Min.	3.25	26.08	55.92	458	33889		Min.	2.12	40.43	48.16	650	35703
BEL	Mean	7.76	39.30	52.95	835	40796	NZL	Mean	6.06	38.30	55.57	362	31627
	Std. dev.	1.08	3.21	3.00	249	4823		Std. dev.	1.93	4.18	3.17	93	4662
	Max.	9.65	44.20	58.88	1402	47541		Max.	10.67	44.13	59.78	532	38993
	Min.	5.36	33.97	48.94	498	32672		Min.	3.60	32.36	51.01	223	23660
CAN	Mean	7.81	37.78	54.36	755	42748	NOR	Mean	4.13	41.98	53.90	1389	82117
	Std. dev.	1.56	2.85	1.78	145	6812		Std. dev.	1.00	4.84	4.37	274	10047
	Max.	11.38	41.70	56.82	926	51589		Max.	6.31	49.60	59.00	2037	92556
	Min.	5.66	33.21	51.39	499	32503		Min.	2.49	36.04	46.33	920	60227
DNK	Mean	6.15	39.41	54.42	1385	55826	PRT	Mean	7.80	25.48	66.73	206	20978
	Std. dev.	1.77	3.74	3.11	425	5886		Std. dev.	3.51	3.91	6.19	96	2165
	Max.	10.72	43.50	59.88	2017	65147		Max.	16.18	33.39	75.50	350	24590
	Min.	3.43	32.74	50.43	677	44569		Min.	3.82	20.31	55.97	77	16668
FIN	Mean	9.94	39.23	50.75	1244	41578	ESP	Mean	17.11	24.81	58.08	306	28509
	Std. dev.	3.40	2.59	1.81	380	6735		Std. dev.	5.35	3.86	4.87	91	3479
	Max.	17.00	42.69	55.77	1754	49441		Max.	26.09	29.20	66.84	422	33350
	Min.	3.07	34.45	48.39	607	29684		Min.	8.23	17.23	49.22	176	22513

Country	Statistics	U (%)	HSE (%)	LSE (%)	RD ($)	GDP ($)	Country	Statistics	U (%)	HSE (%)	LSE (%)	RD ($)	GDP ($)
FRA	Mean	9.77	35.34	54.88	842	38684	SWE	Mean	6.58	41.37	52.00	1589	47708
	Std. dev.	1.52	4.53	3.97	78	3674		Std. dev.	2.28	4.00	3.73	308	7618
	Max.	12.59	41.11	62.43	975	44317		Max.	10.36	48.20	59.32	2023	57975
	Min.	7.06	28.44	49.63	736	32524		Min.	1.83	36.00	46.22	948	35495
DEU	Mean	7.19	37.90	54.91	1027	39769	CHE	Mean	3.84	43.18	52.99	1958	70139
	Std. dev.	2.31	3.34	2.87	240	4626		Std. dev.	0.87	4.98	5.72	449	6080
	Max.	11.17	43.01	62.20	1499	47628		Max.	4.92	50.19	64.66	2718	79407
	Min.	3.14	32.38	51.34	730	32427		Min.	1.78	33.73	45.32	1440	61603
IRL	Mean	9.27	33.18	57.48	584	46863	GBR	Mean	6.47	39.36	54.15	618	37064
	Std. dev.	4.33	5.41	3.57	213	15158		Std. dev.	1.85	4.34	3.56	77	5070
	Max.	15.78	39.35	63.11	928	79703		Max.	10.35	46.49	58.88	758	43688
	Min.	3.68	23.50	49.83	193	24315		Min.	3.74	32.91	48.18	498	28291
ISR	Mean	9.30	36.71	53.99	1093	28446	USA	Mean	5.84	38.65	55.49	1207	45843
	Std. dev.	3.12	8.26	5.90	360	3965		Std. dev.	1.60	2.04	2.17	213	5970
	Max.	14.08	49.78	63.59	1777	35293		Max.	9.63	41.65	58.52	1599	55670
	Min.	3.90	24.77	46.05	538	21520		Min.	3.67	34.94	49.73	878	35542
ITA	Mean	9.96	29.76	60.25	402	34904	TOT	Mean	7.38	36.25	56.34	948	43534
	Std. dev.	1.85	5.09	4.18	57	2136		Std. dev.	3.76	7.25	6.57	508	14661
	Max.	12.68	38.23	68.37	505	38272		Max.	26.09	50.19	78.52	2718	92556
	Min.	6.08	22.30	55.65	308	30871		Min.	1.78	17.23	45.32	77	16668

Source: Authors' calculations.

Since we are interested in the analysis of unemployment technology relation for low skilled workers also, we specified (3). In this equation, LSE_{it} indicates Low Skilled Employment rates. Skill-biased technology approaches that ignore the middle class suggest that unskilled workers may lose their jobs because of technological progress. In addition, approaches like job polarization claim that middle-class workers may lose their jobs, but low-skill workers are not affected by technology negatively since they keep on working more with even lower wages. Since we merged the middle and low classes, we expect the coefficient of RD_{it} negative, because the weight of the middle class is so high compared to the low class. This assumption does not contradict both approaches.

Economic growth is expected to influence *LSE* positively the same way it affects *HSE*. Also, the impact of variables like inflation and the real interest rate on the employment of high-skilled and low-skilled labor as well as the overall unemployment may not be the same. For instance, an increase in the real effective exchange rate may increase unemployment since the domestic production will be less competitive as domestic currency appreciates. But this increase will not be the same in all sectors, and the total impact on high and low-skilled laborers will be different.

We execute the unit root test in every time series analysis to secure our analysis from spurious regression. We make use of Im et al. (2003) to figure out the order of integration and use (4) below to test the existence of the unit root with Im – Pesaran – Shin Unit Root Test. The null hypothesis of H_0: $\rho_i = 0$ (for all i; all series in the panel has the unit root) is tested against the alternative of "at least one series does not have the unit root" (H_A: $\rho_i<0$).

$$\Delta y_{i,t} = z_{i,t}\gamma_{i,t} + \rho y_{i,t-1} + \sum_{j=1}^{k_i} \varphi \Delta y_{i,t-j} + \varepsilon_{i,t} \tag{4}$$

After proving that at least one variable is not stationary at its level, we use Pedroni's (1999) panel cointegration approach to question the long-run relation among variables in series. The panel cointegration analysis shows that even if the series of economic variables are not stationary, there may be a linear combination of these series, which can be determined econometrically, to have a long-term relationship. In this context, if the series are integrated at the same order, then there may be cointegration among the series where the regression between them is not spurious. Both Pedroni (1999) and Kao (1999) panel cointegration methods are used for supporting our conclusion further. We estimate (5) above to compute the estimates of the coefficients and residuals. The panel cointegration test of (9) below has the null of H_0: $\rho_i=1$ (no cointegration). While Pedroni allows for heterogeneity of coefficients, Kao's Test assumes homogeneity.

$$\hat{\varepsilon}_{i,t} = \rho_j \hat{\varepsilon}_{i,t-1} + \sum_{j=1}^{k} \varphi \Delta \hat{\varepsilon}_{i,t-k} + v_{i,t} \tag{5}$$

After we highlight that there is a long-term significant relationship among the variables, we make use of the panel DOLS estimator of Pedroni (2001), Kao and Chiang (2001) and

Mark and Sul (2003). Panel DOLS is a parametric approach for long-term equilibrium estimation in which the variables considered can be integrated by eliminating endogeneity and serial correlation. The PDOLS estimate that is used in this study is based on the equation $\tilde{y}_{i,t} = \tilde{X}'_{i,t}\beta + \sum_{j=-q_i}^{r_i} \Delta\tilde{X}'_{i,t+j}\,\delta_i - \tilde{v}_{1it}$. Besides, in order to support the PDOLS findings, the panel FMOLS estimator results are also reported.

3. Estimation results

Testing for the existence of unit roots is required before applying the panel cointegration test. We use the "IPS test" developed by Im et al. (2003) since it enables us to combine individual unit root test results and handle heterogeneity between panels. We also report LLC (Levin et al., 2002) and Fisher-ADF (Maddala and Wu, 1999) tests results.

As reported in Table 3, IPS test results indicate that seven out of eleven variables are nonstationary at levels. All become stationary at their first differences. That means we attain stationarity of all variables at their first differences. We make use of Pedroni's Cointegration Test that requires the same order of integration for all variables, with at least one being stationary at its level. The same degree of integration for most of the variables provides the impression that the panel cointegration test is likely to conclude a stable relation among the variables in the long run.

Table 3. *Results of panel unit root tests*

Variables	IPS		LLC		ADF - Fisher	
	Level	First Difference	Level	First Difference	Level	First Difference
U_t	-4.428	-10.926	-3.445	-9.894	92.877	196.921
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
HSE_t	2.689	-17.085	-1.226	-18.005	23.141	315.131
	[0.996]	[0.000]***	[0.110]	[0.000]***	[0.992]	[0.000]***
LSE_t	-1.492	-15.345	-4.119	-15.283	61.593	286.842
	[0.068]	[0.000]***	[0.000]***	[0.000]***	[0.026]*	[0.000]***
$\ln(RD)_t$	2.048	-12.363	-2.383	-11.609	38.217	229.033
	[0.980]	[0.000]***	[0.009]**	[0.000]***	[0.638]	[0.000]***
$\ln(GDP)_t$	1.2	-11.986	-4.3	-10.799	28.606	215.402
	[0.885]	[0.000]***	[0.000]***	[0.000]***	[0.943]	[0.000]***
$\ln(CPI)_t$	-1.955	-12.428	-6.157	-11.835	73.446	224.465
	[0.025]*	[0.000]***	[0.000]***	[0.000]***	[0.002]**	[0.000]***
$\ln(PRD)_t$	-3.211	-12.596	-8.578	-13.718	80.824	236.499
	[0.001]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
INT_t	-4.163	-18.733	-5.743	-18.91	90.743	359.222
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
$\ln(PUS)_t$	-1.71	-6.826	2.452	-14.097	57.75	137.348
	[0.044]*	[0.000]***	[0.993]	[0.000]***	[0.054]	[0.000]***
$\ln(TUD)_t$	2.692	-13.003	-1.704	-13.57	28.274	227.886
	[0.997]	[0.000]***	[0.044]*	[0.000]***	[0.948]	[0.000]***
$\ln(EXC)_t$	-3.219	-14.861	-2.679	-15.178	79.733	272.091
	[0.001]***	[0.000]***	[0.004]**	[0.000]***	[0.000]***	[0.000]***

Note: The IPS tests for all variables include constant. In order to detect the optimal lag length, the Akaike Information Criterion (AIC) is used. *Rejection of the null of nonstationarity at 0.05 level, **Rejection of the null of nonstationarity at 0.01 level, ***Rejection of the null of nonstationarity at 0.001 level.
Source: Authors' calculations.

Panel cointegration results of Equation (1) with unemployment identified as the dependent variable are summarized in Table 4. In Model 1, ln*(RD)*, ln*(GDP)*, and ln*(CPI)* are used as independent variables. In Model 2, ln*(PRD)* is used in addition to the variables in the first model. We defined these first two models as "baseline specifications". We append *INT*, ln*(PRD)*, ln*(TUD)*, and ln*(EXC)* in the other four models. We present the Kao Panel Cointegration Test results in addition to Pedroni's to support the initial findings. Pedroni Cointegration Test is executed without trend, which rejects the null hypothesis of "no cointegration" in all six models at the 0.05 significance level. In addition, Kao Cointegration Test concludes the same at the 0.01 significance level. In all models, at least three of five cointegration statistics highlight that there is a long-run stable relation among variables.

Table 4. *Results of panel cointegration tests for unemployment*

Test	Statistics	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
		RD, GDP, CPI	*RD, GDP, CPI, PRD*	*RD, GDP, CPI, PRD, INT, PUS*	*RD, GDP, CPI, PRD, INT, TUD*	*RD, GDP, CPI, PUS, TUD, EXC*	*RD, GDP, CPI, PRD, PUS,TUD*
Pedroni	Panel PP t	-0.105	-1.853	-2.055	-3.071	0.510	-2.168
	p-value	[0.458]	[0.032]*	[0.020]*	[0.001]***	[0.695]	[0.015]*
	Panel ADF t	-2.957	-3.708	-2.319	-2.656	-1.734	-3.188
	p-value	[0.002]**	[0.000]**	[0.010]**	[0.004]**	[0.042]*	[0.001]***
	Group PP t	0.257	-1.856	-3.289	-4.342	-2.585	-2.720
	p-value	[0.601]	[0.032]*	[0.001]***	[0.000]***	[0.005]**	[0.003]**
	Group ADF t	-4.346	-3.380	-2.097	-2.985	-1.659	-1.659
	p-value	[0.000]***	[0.000]***	[0.018]*	[0.001]***	[0.049]*	[0.049]*
Kao	ADF t	-6.200	-5.565	-5.735	-5.453	-5.835	-5.854
	p-value	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***

Note: In order to detect the optimal lag length, the AIC is used. In panel PP and ADF results, weighted statistics are reported. In Base Model 1, lnRD_t, lnGDP_t, and lnCPI_t are used as independent variables. Base Model 2 includes lnPRD_t in addition to the variables in Base Model 1. Four extra models are also generated including other independent variables. P-values are given in brackets. *Rejection of the null hypothesis of no cointegration at the 0.05 level, **Rejection of the null hypothesis of no cointegration at the 0.01 level, *** Rejection of the null hypothesis of no cointegration at the 0.001 level.
Source: Authors' calculations.

After proving the existence of the long-run relation empirically, we make use of panel DOLS (Dynamic OLS) to estimate the coefficients of the variables. In addition to panel DOLS estimation, FMOLS (Fully Modified OLS) results are also reported as a robustness check. Results displayed in Table 5 and Table 6 belong to six models established for unemployment. In the analyses, the decimal fraction of U_t is used. Since the number of variables to be included in a panel with short periods has to be limited, we take care of this constraint to elaborate on the equations to keep the number of variables as low as possible. The coefficient vector β has close estimates in six equations, and both panel DOLS and FMOLS estimates of *R&D* are significant at 5%. Based on these results, the coefficient of *ln(RD)* is positive and between 0.012-0.034, which means technology increases overall unemployment. Our findings lead to the very important inference that in developed economies, technological progress makes job creation outweighed by job destruction and the compensation mechanism is not effective. Besides, *ln(GDP)* has a negative coefficient, consistent with the theory and previous empirical studies. The coefficient of *ln(GDP)* ranges between -0.17 and -0.44. The measure of inflation *ln(CPI)* and productivity variable *ln(PRD)* are positively correlated with unemployment.

Table 5. *PDOLS and FMOLS estimates results for the baseline specifications,* ***Dependent variable: U_t***

Variables	Model 1 (Base Model 1)				Model 2 (Base Model 2)			
	PDOLS		FMOLS		PDOLS		FMOLS	
	Beta	t-stat	Beta	t-stat	Beta	t-stat	Beta	t-stat
$ln(RD)_t$	0.032	4.429***	0.034	3.706***	0.021	5.026***	0.022	3.938***
$ln(GDP)_t$	-0.217	-14.426***	-0.174	-8.090***	-0.440	-29.208***	-0.403	-20.446***
$ln(CPI)_t$	0.067	5.529***	0.038	2.609**	0.046	5.789***	0.044	5.241***
$ln(PRD)_t$					0.376	18.271	0.341	14.042***

Note: For the PDOLS estimator, the AIC is used to determine the leads & lags and the pooled-weighted estimation is used as panel method. For the FMOLS estimator, sandwich method is used in estimating covariance. As the dependent variable, decimal fractions of U_t are used. *Significance at the 0.05 level, ** Significance at the 0.01 level, ***Significance at the 0.001 level.
Source: Authors' calculations.

In terms of studies on the relationship between inflation and unemployment at macro level, on the one hand, the classical Philips Curve reveals the existence of a negative relationship; on the other hand, numerous empirical studies in the literature suggest the existence of a positive, insignificant or a negative relationship. In this study, it is concluded that inflation has a positive impact on total unemployment in the long run. In addition, the coefficient of *ln(TUD)* is positive and significant in the two models while insignificant in one model. Since the higher share of trade unions increases the wages, employers may want to hire fewer workers. These findings are in line with Soskice (1990) and Baccaro and Rei (2007). We also find a positive and significant impact of real interest rate in one PDOLS and two FMOLS estimates, while it is insignificant in one PDOLS model. On the other hand, the effect of *ln(REER)* is negative but insignificant according to PDOLS results.

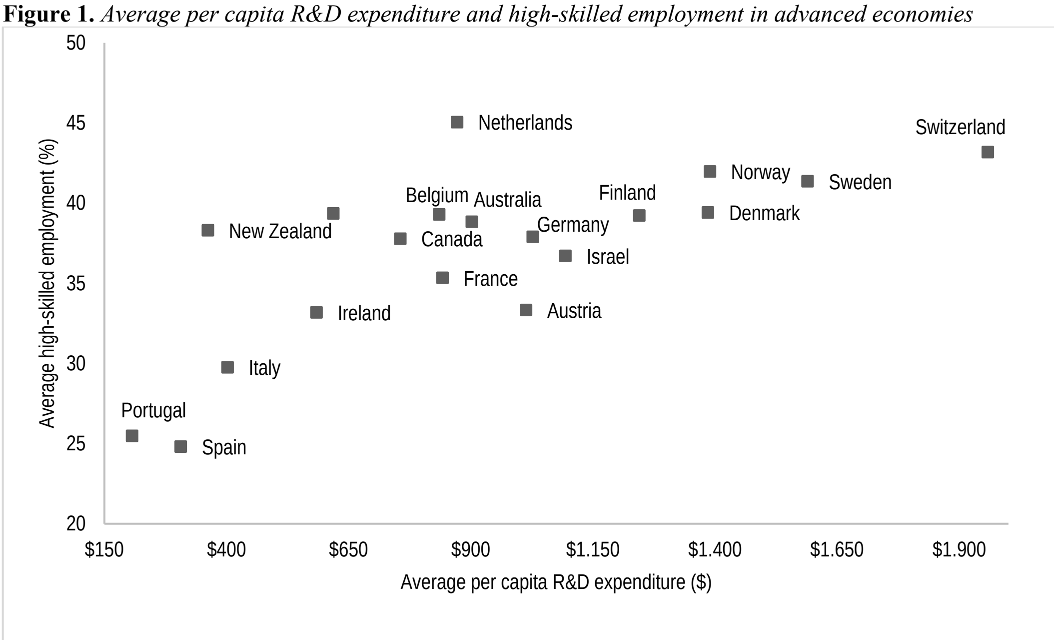
Table 6. *PDOLS and FMOLS estimates results for the additional models. Dependent variable: U_t*

Variable	Model 3		Model 4		Model 5		Model 6	
	PDOLS	FMOLS	PDOLS	FMOLS	PDOLS	FMOLS	PDOLS	FMOLS
$ln(RD)_t$	0.012	0.015	0.026	0.023	0.022	0.025	0.014	0.019
	(2.454)**	(3.079)**	(4.663)***	(4.714)***	(2.216)*	(3.327)***	(2.628)**	(3.793)***
$ln(GDP)_t$	-0.381	-0.364	-0.402	-0.374	-0.168	-0.135	-0.413	-0.372
	(-19.148)***	(-19.269)***	(-23.958)***	(-24.572)***	(-6.569)***	(-7.312)***	(-24.489***	(-23.502)***
$ln(CPI)_t$	0.052	0.045	0.052	0.050	0.068	0.022	0.058	0.042
	(5.070)***	(5.558)***	(5.096)***	(7.010)***	(4.035)***	(1.835)	(5.526)***	(5.634)***
$ln(PRD)_t$	0.326	0.322	0.351	0.328			0.400	0.330
	(13.265)***	(14.234)***	(13.042)***	(18.606)***			(17.081)***	17.753)***
INT_t	0.001	0.001	0.001	0.001				
	(1.573)	(2.778)**	(2.599)**	(4.913)***				
$ln(PUS)_t$	0.006	0.009			0.014	0.016	0.008	0.009
	(1.505)	(5.231)***			(4.154)***	(6.814)***	(2.264)*	5.226)***
$ln(TUD)_t$			0.025	0.018	0.008	-0.004	0.036	0.011
			(2.567)*	(2.970)**	0.686	(-0.443)	(3.795)***	(1.683)
$ln(EXC)_t$					-0.012	-0.022		
					(-0.939)	(-2.606)**		

Note: For the PDOLS estimator, the AIC is used to determine the leads and lags, and the pooled-weighted estimation is used as the panel method. For the FMOLS estimator, the sandwich method is used in estimating covariance. As the dependent variable, decimal fractions of U_t are used. Except for interest rate, all independent variables are in natural logs, and t-statistics are given in parentheses. *Significance at the 0.05 level, **Significance at the 0.01 level, ***Significance at the 0.001 level.
Source: Authors' calculations.

In addition to the technology unemployment relation, we are interested in detailing this relation to different skill groups. Both skill-biased technological change approaches and comments on job polarization claim that the impact of technology on high or low-skilled workers is varying. In this regard, Figure 1 is illustrative and visualizes a clear picture of this difference. Per capita R&D expenditures and high-skilled employment rates are spotted over a 30-year horizon with averages for developed economies. The graph illustrates that as per capita R&D increases, high skilled employment rates also increase, which is very reasonable. Spain and Portugal have the lowest average high-skilled employment rate with the lowest average R&D expenditure.

Figure 1. *Average per capita R&D expenditure and high-skilled employment in advanced economies*



We enlarge our analysis to account for the skill levels with the same methodology and procedure of Equations (1), (2), and (3). To this end, Table 7 reports panel cointegration test results of four models. The null hypothesis with and without trend is rejected at 5% significance level for all models, underlining the long-term relationship. Kao cointegration test results support Pedroni's again. These results document that in developed countries, both high-skilled and low-skilled employment rates have a long run significant relation with R&D and other macro variables included.

Table 7. *Results of panel cointegration tests for employment by skill levels*

Test	Statistics	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
		RD, GDP, CPI	*RD, GDP, CPI, PRD*	*RD, GDP, CPI, PRD, INT,*	*RD, GDP, CPI*	*RD, GDP, CPI, PRD*	*RD, GDP, CPI, PRD, INT,*
		Dependent variable: HSE_t			**Dependent variable:** LSE_t		
Pedroni	Panel PP t	-2.529	-2.711	-2.868	-1.581	-2.002	-3.421
	p-value	[0.006]**	[0.003]**	[0.002]**	[0.057]	[0.023]*	[0.000]***
	Panel ADF t	-4.046	-4.569	-5.008	-3.410	-3.914	-3.508
	p-value	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
	Group PP t	-2.566	-3.225	-3.467	-1.107	-2.557	-4.331
	p-value	[0.005]**	[0.001]***	[0.000]***	[0.134]	[0.005]**	[0.000]***
	Group ADF t	-4.768	-4.625	-4.203	-3.106	-3.881	-3.449
	p-value	[0.000]***	[0.000]***	[0.000]***	[0.001]***	[0.000]***	[0.000]***
Kao	ADF t	-1.648	-1.807	-2.837	-3.911	-3.671	-3.804
	p-value	[0.050]*	[0.035]*	[0.002]**	[0.000]***	[0.000]***	[0.000]***

Note: In order to detect the optimal lag length, the AIC is used. In panel PP and ADF results, weighted statistics are reported. In Model 7 and Model 11, $\ln RD_t$, $\ln GDP_t$, and $\ln CPI_t$ are used as independent variables. Model 8 and Model 11 include $\ln PRD_t$, and Model 9 and Model 12 include both $\ln PRD_t$ and INT_t. in addition to the variables in baseline models. P-values are given in brackets. *Rejection of the null hypothesis of no cointegration at the 0.05 level, **Rejection of the null hypothesis of no cointegration at the 0.01 level, ***Rejection of the null hypothesis of no cointegration at the 0.001 level.
Source: Authors' calculations.

We go one step ahead after proving the existence of the long-run nexus among variables of interest to diagnose the direction and magnitude of the relation. Estimation results of PDOLS are reported in Table 8. Coefficients of R&D in models (7), (8), and (9) established for high-skilled employment are positive, while corresponding coefficients in models (10), (11), and (12) established for low-skilled employment are negative, and the coefficients in all six models are significant. These results are in line with the assertion that the impact of technological progress shock on employment is skill-biased. On the other hand, the rise in per capita GDP increases both high-skilled and low-skilled employment. Besides, it is concluded that an increase in productivity decreases especially low-skilled employment instead of high-skilled. Just like R&D expenditure, the impact of inflation on high and low skilled labor is contradictory since inflation is known to be increasing due to demand-pull as economic activity revives. The interesting conclusion is that our results on the high-skilled employment effect of inflation are parallel with the classical Philips Curve, while low-skilled employment is not. Finally, the real interest rate has a negative impact on high-skilled employment while it is insignificant in explaining low-skilled employment.

Table 8. *Panel DOLS estimates results of the long-run relationship for employment by skill levels*

Variables	Dependent Variable: HSE_t			Dependent Variable: Low LSE_t		
	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
$\ln(RD)_t$	0.042	0.050	0.052	-0.040	-0.049	-0.065
	(4.438)***	(5.011)***	(4.945)***	(-3.130)**	(-4.030)***	(-5.456)***
$\ln(GDP)_t$	0.112	0.112	0.125	0.084	0.239	0.237
	(5.092)***	(3.868)***	(3.631)***	(3.625)***	(6.659)***	(6.068)***
$\ln(CPI)_t$	0.055	0.048	0.050	-0.129	-0.112	-0.113
	(3.531)***	(2.653)**	(2.464)**	(-5.864)***	(-5.289)***	(-5.029)***
$\ln(PRD)_t$		-0.018	-0.080		-0.256	-0.210
		(-0.687)	(-2.306)*		(-6.531)***	(-4.813)***
INT			-0.002			0.002
			(-2.117)*			(1.944)

Note: For the PDOLS estimator, the AIC is used to determine the leads and lags, and the pooled-weighted estimation is used as the panel method. As the dependent variable, decimal fractions of HSE_t and LSE_t are used. Except for interest rate, all variables are in natural logs, and t-statistics are given in parentheses. *Significance at the 0.05 level, ** Significance at the 0.01 level, *** Significance at the 0.001 level.
Source: Authors' calculations.

4. Concluding remarks

We make use of annual data from 21 developed countries over 1990-2019 to document that there is cointegration among the set of variables including R&D expenditures and (un)employment. Our time span includes the hit of the global financial crisis to reveal the resilience of the relationship even along with the shock and thereafter. We detail the analysis to explore the impact of technology on the employment of high and low-skilled labor. Estimation results with PDOLS and FMOLS demonstrate that:

a) As R&D expenditures increase, employment of the high-skilled workers increases, whereas the opposite is true for the low-skilled workers in advanced economies. The compensation mechanism is effective for high skilled workers, not the low skilled ones.
b) R&D expenditures increase total unemployment, even in developed economies. The possible reason for this result is that in developed countries, the intensity of skilled workers is still less than the intensity of unskilled or low-skilled employees. If low-skilled workers become more equipped and are able to adapt to new technologies, the impact of technology on overall unemployment may reverse in the future.
c) Growth declines unemployment as expected.
d) To the contrary, productivity increases unemployment.
e) Public unemployment spending and unemployment are positively related as the positive coefficients of *PUS* suggest.

Our investigation asserts concrete empirical evidence on the research and development expenditure unemployment relation coupled with skill groups, but further analyses are required, and there is room to explore the same relation along with other key variables headed by wage and working conditions.

Note

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